

Using Bayesian Networks to assess the risk appetite of construction contractors

Cattell, David; Love, Peter

Published in:
38th Australian University Building Educators Association Conference

Licence:
Unspecified

[Link to output in Bond University research repository.](#)

Recommended citation(APA):
Cattell, D., & Love, P. (2013). Using Bayesian Networks to assess the risk appetite of construction contractors. In *38th Australian University Building Educators Association Conference* (pp. 1-11). University of Auckland.

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

For more information, or if you believe that this document breaches copyright, please contact the Bond University research repository coordinator.

USING BAYESIAN NETWORKS TO ASSESS THE RISK APPETITE OF CONSTRUCTION CONTRACTORS

D.W. Cattell¹, P.E.D. Love²

¹Bond University, Gold Coast, Queensland, Australia

²Curtin University, Perth, Western Australia

Corresponding author: dcattell@bond.edu.au

ABSTRACT

The pricing of items of construction work using Component Unit Pricing (CUP) Theory requires that contractors have to assess and quantify their risk profiles. Those contractors with a willingness to take on greater risks can then be rewarded with a prospect of greater profits. CUP Theory provides a basis by which this can be accomplished by way of the manner and extent to which contractors spread their overall bid prices amongst all of the constituent component item prices. Conversely, this theory also facilitates that contractors who want to moderate their exposure to risk are able to do so, independently of any adjustment they might choose to make to their overall mark-ups. Contractors are, however, typically unaware of their risk profiles and will not have had these assessed. There are no universally accepted or popular methods established for the assessment of the risk profiles of firms operating within the construction industry. Bayesian networking (BN) is gaining popularity in the financial management arena as a sophisticated statistical approach for the assessment and management of risks. It is envisaged that it might serve well for evaluating and explaining contractors' risk profiles as well as facilitate a process by which these can be reviewed and modified in line with inevitable changes over time. Against this contextual backdrop this paper provides an overview as to how BNs can be used to improve the risk profiles of contractors.

INTRODUCTION

New methods of item pricing have identified prospects of considerable additional profits for contractors, relative to the default scenario of 'balanced bid' pricing (Cattell, 2012). Item pricing (in the sense of deciding the distribution of the overall project price amongst the constituent items by way of their unit prices) does, however, affect the contractor's exposure to risk. Component Unit Pricing (CUP) Theory provides a basis to facilitate the estimation of both the expected profit and the risk of any pricing scenario (Cattell, 2012). The modelling of profit and risk serves to guide this decision. As is

typical of many financial analyses, a wide spectrum of alternative (in this case, pricing) scenarios can be identified in which each can have quite-considerably different risks and rewards associated with them. Markowitz's Modern Portfolio Theory (1990) suggests that most of these options should be discarded and that a small subset of these can be filtered out (which Markowitz declared as the 'efficient' ones) that render all of the others as comparatively unattractive, illogical choices. Efficient pricing scenarios offer the most expected profit relative to their risk, and correspondingly also the least risk for that degree of expected profit. There should be no reason for a contractor not to want to adopt one of these sets of prices. This process of filtering out all of the inefficient pricing scenarios can significantly reduce the options and help refine and focus the decision that has to be made, but it still leaves a wide spectrum of choice. These range from ones that yield the appeal of low-risk (albeit with the expectation of only low profits) through to the appeal of high-profit yields (with high risks though). All of these Efficient choices are logically appealing choices and there is genuine prospect for a rational justification for any one of these. There is no obvious preference for one of these over the others, unless and until the contractors take account of their risk profile. If, for instance, the contractor has an appetite for high risks, their best (high-yielding) choice will become more obvious. Thus, any such analysis needs to be based on knowledge of the contractor's attitude to risk, else no single pricing decision will emerge as being optimal.

This nature of decision in the mainstream commercial arena (having no particular reference to construction nor to the aspect of pricing) has been thoroughly researched in recent decades with (Nobel-prize winning) leadership by Kahneman and Tversky (1979). Their field of Prospect Theory, and its various derivatives, are based on recognition that, with knowledge of the 'risk profile' of each economic player, the objective can be identified as the maximisation of any such player's derived Utility, recognising that this entails some combination of maximising profit whilst simultaneously seeing to minimise risk. There is no known history of determining the risk profiles of construction contractors. It is hereby suggested that the field of Bayesian networks (BN) may be appropriate for doing so, especially during the tender process. In this instance 'price certainty' becomes a fallacy as complete drawings and bills of quantities are generally not available when a project goes to tender. The pressure to complete contract documentation and go to tender at the earliest date is a common cause of problems in modern projects (Tilley and McFallan, 2000). As a result, very few projects are completed within their tender price (Rowlinson, 1999).

BAYESIAN NETWORKS

A Bayesian Network is a way of describing the relationships between cause and effects and is comprised of nodes and arcs as noted in Figure 1. The arcs in a BN represent a 'causal' or 'influential' relationship between variables. Thus, 'incomplete' contract documents can cause and/or influence both contractor A and B to submit uncompetitive tenders due to potential risks. A key feature of BNs is that it can enable uncertainty to be modelled. In the simple example presented, incomplete documents do not imply that an uncompetitive tender is submitted, but there is an increased probability it could be high.

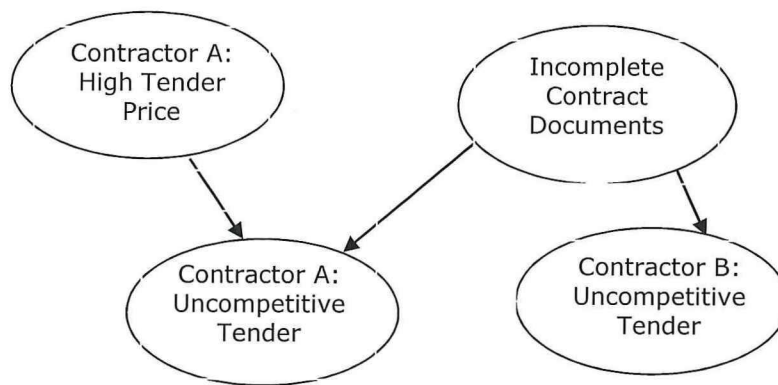


Figure 1. Simple BN

This information is captured for the node in the Node Probability Table (NPT) presented in Table 1. The NPT provides the conditional probability of each possible outcome given each combination of outcomes for its parent nodes. In this case of 'contractor B' providing an uncompetitive bid has one parent node "incomplete contract documents". Table 1 reveals the probability contractor B will be...

- uncompetitive, given a situation where the contract documentation is incomplete, is 0.8;
- *not* uncompetitive, given that there is incomplete documentation is 0.2;
- uncompetitive, given that the probability that the documentation is complete is 0.1; and
- not uncompetitive, given that the probability the documentation is complete is 0.9.

Table 1. NPT for an uncompetitive tender for contractor B.

Incomplete Contract Documents	False	True
False	0.9	0.2
True	0.1	0.8

In the case of contractor A having an uncompetitive tender is presented in Table 2. Here, the situation describing contractor A has two parents involved and so the number of combinations of parent states is four rather than two. The NPTs for the root nodes are presented in Table 3. In the case of the root nodes there are only two possible values 'true' or 'false'.

Table 2. NPT for an uncompetitive tender for contractor A

Contractor A's High Tender Price	False		True	
Incomplete Contract Documents	False	True	False	True
False	0.7	0.4	0.4	0.2
True	0.3	0.6	0.6	0.8

Table 3. NPTs for the root nodes

NPT for incomplete documents	
False	0.9
True	0.1

Contractor A's high tender price	
False	0.6
True	0.4

There are several ways in which probabilities can be determined in any of the tables. For example, the NPT for 'incomplete contract documents' reflects the same as for previously observed frequencies

for incomplete documentation for previous projects. Alternatively, if no such statistical data is available then subjective probabilities can be used. A key feature of BNs is that they can cater for subjective probabilities and those based upon objective data. To determine if contractor B's tender is uncompetitive, then intuitively, the probability of incomplete contract documents must have increased from its prior value of 0.1. The question is in this instance by how much? Using Bayes Theorem, which is defined as:

$$P(T|N) = \frac{P(N|T)P(T)}{P(N)} \quad \text{Eq.1}$$

From the NPT it is known that $P(N|T) = 0.8$ and that $P(T) = 0.1$. Thus, the numerator in Bayes Theorem, in this instance, is 0.08. The denominator, $P(N)$ is referred to as an unconditional probability that contractor B is uncompetitive. This essentially means the probability contractor B is uncompetitive when no specific information about the completeness of the documentation is provided. The NPTs do not provide this value directly, but it can be derived indirectly using the following equation:

$$P(N) = P(N|T)P(T) + P(N|\sim T)P(\sim T) \quad \text{Eq.2}$$

Thus, $P(N) = 0.8(0.1) + 0.1(0.9)$, which = 0.17. Substituting this derived value of $P(N)$ into Eq.1 then $P(T|N) = 0.08/0.17 = 0.471$. The observation that contractor B is uncompetitive significantly increases that the contract documentation is incomplete (an increase from 0.1 to 0.471). Contractor A is conditioned by two events so to also determine if they are uncompetitive. O is introduced to represent their high tender price. Thus the marginal probability for contractor A being uncompetitive is:

$$\begin{aligned} P(M) = & P(M|T,O)P(T)P(O) \\ & + P(M|T, \sim O)P(T)P(\sim O) \\ & + P(M|\sim T,O)P(\sim T)P(O) \\ & + P(M|\sim T, \sim O)P(\sim T)P(\sim O) \end{aligned} \quad \text{Eq.3}$$

Thus, $P(M) = 0.032 + 0.036 + 0.216 + 0.162$, which = 0.446.

The revised marginal $P(T) = 0.471$ and thus $P(\sim T) = 0.529$. Using the values in the equation above, the observation that contractor B is also uncompetitive has also increased the probability that contractor A is uncompetitive.

Notice that Bayesian networks cater for causal-effect relationships that are discrete (true or false) and also all those that entail continuous-scale probabilities. For instance, it does not necessarily follow, for certain, that because the sun is now shining that it won't be raining this afternoon. The fact that the sun is shining might

lessen the odds of it raining this afternoon, but it does not discount the possibility altogether. Nevertheless, knowing that the sun is now shining may be useful knowledge if one is trying to determine the likelihood of rain this afternoon. It is presumably more likely to rain soon if it is cloudy than if it is sunny. Furthermore, other observations may also be useful in predicting rain this afternoon, such as how often it has rained recently, and particularly so during the hours of the afternoon, and how frequently it rains at this time of year, based on a statistical analysis of the climate over many years. BN facilitate that all this data can be taken into account when predicting rain as well as perhaps the opinions of local experts and of meteorologists.

In terms of construction, a project may be more likely to be delayed if its foundations are being built in the rainy season than in a dry season. However, it does not follow that if the project is being built in a wet season that it will definitely be delayed or that if it is being built in a dry season that it will not be. BNs appear to be very good at dealing with situations like this, particularly when the models involved are complex and comprise many such variables / causes, interconnected in a wide variety of ways. It can accept data as regards these causal-effect connections in ways that make them practical to implement. For instance, some of these probabilities could be informed by way of statistical analyses of past projects and others could be informed by way of expert opinion. Combinations of several such inputs are also possible. As mentioned above, 'soft' subjective opinions can be interspersed with 'hard' relatively-indisputable objective data. Gaps in knowledge can be easily filled.

Benefits of BNs

BN enjoys several significant benefits that are noteworthy. Firstly, they facilitate being reviewed on a dynamic basis. As new data arises, networks can be updated and new output generated, typically without even having to recalculate the entire network but rather only by way of focussing on those areas that are affected. Secondly, BN are structured that they are transparent and auditable, and do not function as opaque 'black boxes'. They explain how the end result is accomplished and what the significant contributions were, that gave rise to this. Thus they facilitate that these most-sensitive variables can then be reviewed and refined in the light of the discovery of their significance. Thirdly, they facilitate 'back-propagation', or in other words, they can fairly-easily show what input values might be that would generate any desired output. These attributes encourage modellers to be able to dive in and gain greater insight into how and why their models are operating than if they were simply a one-way opaque black-box in which some input simply (in some unknown

manner) leads to the desired output. BN is, by contrast, a dynamic and flexible beast that invites one to engage with and play with it.

It is proposed that BN appears well suited for the purpose of assessing a contractor's risk profile. Risk profiles are typically derived from interviews. These interviews entail participants having to choose between options to the extent that the process can identify their 'indifference map'.

Trade-off between Risk and Reward

Webster (2003) and Besley and Brigham (2007) give examples of this. In essence, as was explained by Cattell (2012), a company's risk profile reflects the perception their management has of the acceptable trade-off between risk and the reward required to compensate them for taking these risks. This technique can then be used to predict such persons' *certainty equivalence* of a wider variety of options. With this knowledge, one can determine a person's *indifference map* (see Figure 2), taking account of different levels of risk. An indifference map comprises as many as an infinite series of *indifference curves*. Figure 2 shows an indifference map comprising three indifference curves - each curve representing the contractor deriving the same level of utility from alternative combinations of expected return and risk. The theory is that a contractor should prefer all options on curve I_3 to all of those depicted on curve I_2 , and so on. However, they should be indifferent as regards choosing any of the options depicted on any one of these curves.

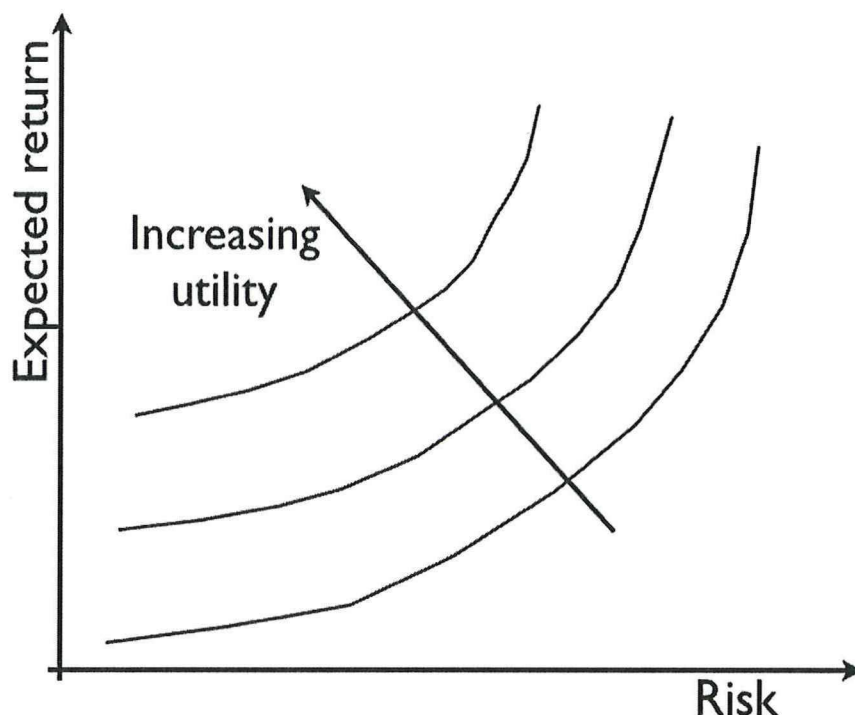


Figure 2 Indifference map, comprising 3 indifference curves, each representing a constant level of utility

Figure 3 shows the indifference maps for two contractors, A and B. In this instance, contractor B is showing that they are less risk-averse than contractor A. For any given level of risk, contractor A has a greater need for a higher return than contractor B, to compensate them for taking on this degree of risk. Point 'X' shows the risk-free rate of return that both A and B require, shared in common because there is no risk involved (Besley and Brigham, 2007.)

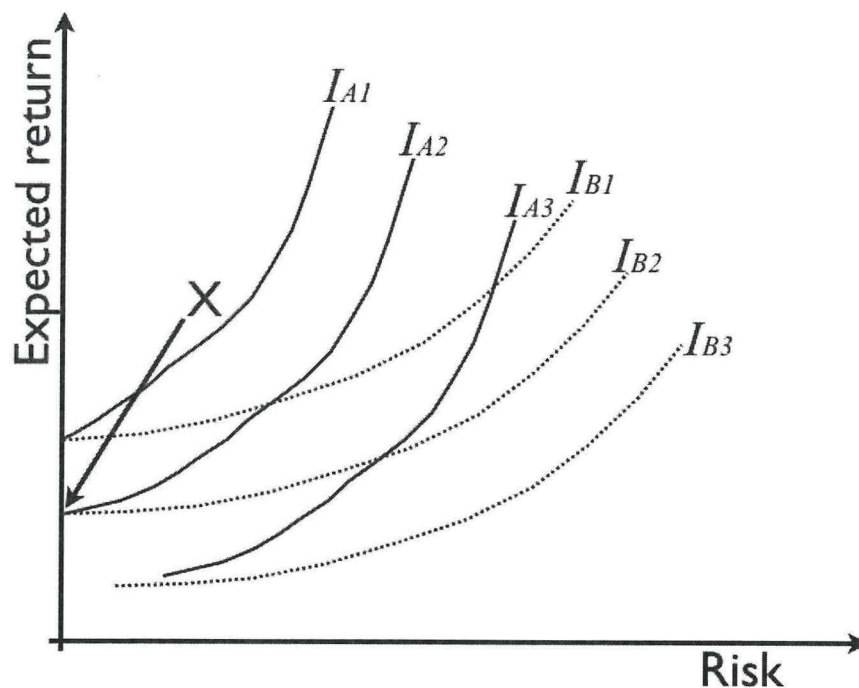


Figure 3 Indifference maps for two contractors, A and B.

If a contractor has had their risk profile assessed and if one then knows their *indifference map*, then the knowledge of this can be combined with that of a project's *efficient frontier* (that MPT has provided) (Markowitz, 1990). In combination, one can then identify the single (efficient) item pricing combination that represents the contractor's *optimal* choice of pricing for a project, giving them a greater *utility* than all other possible item prices (Besley and Brigham, 2007). This is shown in Figure 4, where contractor A's optimal portfolio is depicted as 'M' whereas contractor B's optimal portfolio is 'N'. Notice that contractor B will not only be deriving more return from their optimal portfolio than contractor A, but also that they will be accomplishing greater satisfaction (ie. *utility*) as well, despite incurring greater risk.

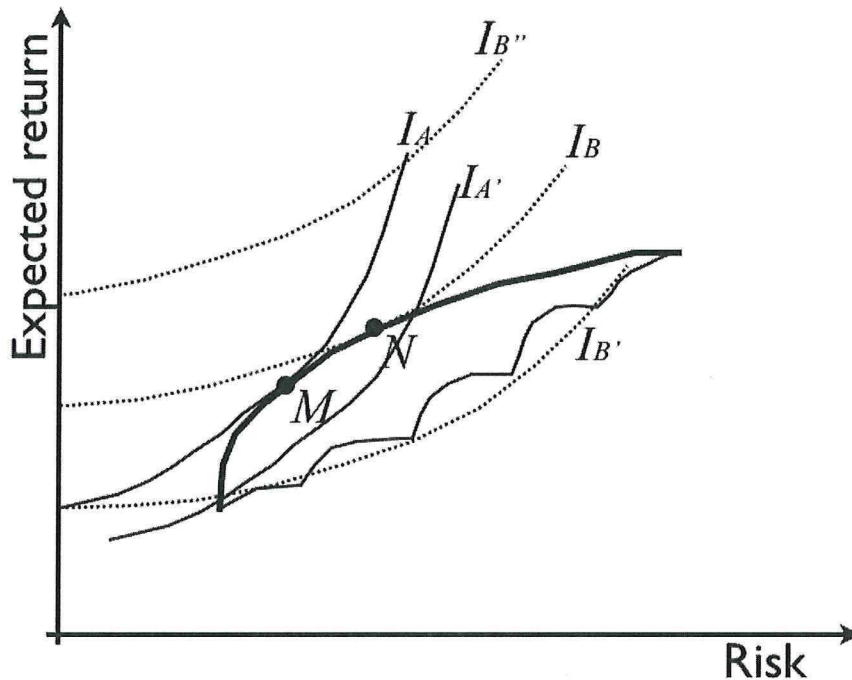


Figure 4. Optimal Portfolio Selection

CONCLUSION

Contractors have need to assess their risk profiles if they are to take advantage of new item pricing techniques such as those facilitated by way of Component Unit Pricing (CUP) Theory. The benefits from doing so have been identified as considerable, both from the perspective of the potential increase in profits as well as from the perspective of risk management. Contractors have, however, not typically quantified or formally reviewed their attitude to risk vs. return. It is proposed that Bayesian networking seems suited to being used for this purpose and that this warrants further research.

REFERENCES

- Al-Momani, A. (2000). 'Examining service quality within construction processes', Elsevier, *Technovation*, vol. 20, pp. 643-651.
- Albright, S., Winston, W., Zappe, C. (2009). *Data analysis & decision making, with Microsoft Excel*, revised 3rd ed., Mason: South-Western.
- Barber, D. (2012). *Bayesian reasoning and machine learning*, New York: Cambridge.
- Besley, S. and Brigham, E.F. (2007). *Essentials of managerial finance*. 14th.ed., Cengage South-Western. ISBN: 0-324-42270-9.
- Bolstad, W. (2007). *Introduction to Bayesian statistics*, 2nd ed., Hoboken: Wiley.
- Cattell, D. (2012). *Construction item pricing – for more profit and less risk*. Cape Town: UCT Press.

- Davis, P., Love, P., Baccarini, D. (2009). 'Bills of quantities: nemesis or nirvana?', *Emerald, Structural Survey*, vol. 27, no. 2, pp. 99-108.
- Efron, B. (2010). *Large-scale inference: empirical Bayes methods for estimation, testing, and prediction*, New York: Cambridge.
- Ewerhart, C., Fieseler, K. (2003) 'Procurement auctions and unit-price contracts', *RAND Journal of Economics*, vol. 34, no. 3, pp. 569-581.
- Fenton, N., Nell, M. (2007). 'Managing risk in the modern world', A Knowledge Transfer Report from the London Mathematical Society and the Knowledge Transfer Network for Industrial Mathematics, London: London Mathematical Society.
- Fenton, N., Nell, M. (2013). *Risk assessment and decision analysis with Bayesian networks*, Boca Raton: CRC Press.
- Grover, J. (2013). *Strategic economic decision-making: using Bayesian networks to solve complex problems*, New York: Springer.
- Kahneman, D. (2002). Maps of bounded rationality. *Prize Lecture*. The Nobel Foundation. Available at http://nobelprize.org/nobel_prizes/economics/laureates/2002/kahneman-lecture.html [accessed 12th May, 2009].
- Kahneman, D. and Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica*, XLVII, pp. 263-291.
- Kahneman, D. and Lovallo, D. (1993). Timing choices and bold forecasts: a cognitive perspective on risk taking. *Management Science*, vol.39, no.1, pp. 17-31. Available at http://www.som.yale.edu/faculty/keith.chen/negot.%20papers/KahnemanLovallo_ChoiceForecastsRisk93.pdf [accessed 12th May, 2009].
- Korb, K. and Nicholson, A. (2011). *Bayesian artificial intelligence*, 2nd ed., Boca Raton: CRC Press.
- Kwak, Y., Walewski, J., Sleeper, D., Sadatsafavi, H. (2013) 'What can we learn from the Hoover Dam project that influenced modern project management', Elsevier, *International Journal of Project Management*, [<http://dx.doi.org/10.1016/j.ijproman.2013.04.002>]
- Lyons, T., Skitmore, R.M. (2004). 'Project risk management in the Queensland engineering construction industry: a survey', *International Journal of Project Management*, Vol. 22 (1), pp.51-61.
- Mandell, S., Nylström, J. (2011) 'Why are bids not more unbalanced?', Working papers in Transport Economics, CTS - Centre for Transport Studies Stockholm (KTH and VTI), no. 13.
- Markowitz, H.M. (1990). Foundations of portfolio theory. *Nobel lectures in economic sciences 1981-1990*. Ed. Karl-Göran Mäler, World Scientific, pp. 279-288.
- Pearl, J. (1985). 'Bayesian networks: a model of self-activated memory for evidential reasoning', *Proceedings of the 7th*

- Conference of the Cognitive Science Society, University of California, Irvine, CA. pp. 329–334.
- Rowlinson, S. (1999). The definition of procurement systems. In S. Rowlinson and P. McDermott (Eds.), *Procurement Systems: A Guide to Best Practice in Construction*. E&F Spon, London, pp.27-53.
- Shrestha, P., Shrestha, K., Joshi, V. (2013). 'Investigation of unbalanced bidding for economic sustainability', *ASCE, ICSDEC 2012: Developing the Frontier of Sustainable Design, Engineering, and Construction*, pp. 609-616. [<http://dx.doi.org/10.1061/9780784412688.073>]
- Tilley, P. A., and McFallan, S. L. (2000). Design and Documentation Quality Survey Comparison of Designers' and Contractors' Perspectives. BCE DOC 00/115, CSIRO Building, Construction and Engineering, Melbourne, Australia
- Webster, T.J. (2003). *Managerial economics: theory and practice*. New York: Academic Press.